Discovering and Visualizing Differences of DTI Fiber Models

Category: Research

ABSTRACT

Fiber tracking of Diffusion Tensor Imaging (DTI) datasets is a non-invasive tool to study the underlying fibrous structures in living tissues. However, DTI fiber models may vary from subject to subject due to variations in anatomy, motions in scanning, and signal noise. In addition, fiber tracking algorithms and parameters also have a great influence on the tracking results. Interactive exploring and analysing the differences among DTI fiber models is critical for the purpose of group comparison, atlas construction, and uncertainty analysis. Standard approaches illustrate differences in the 3D space with either voxel-wise or fiber-based comparisons. This paper introduces a cluster-projection routine to embed a complex 3D fiber model as a continuous map in a 2D comparison space. To facilitate exploration, regions of significant differences among the 2D maps are further identified. Using these maps, subtle differences that are difficult to be distinguished in the 3D space due to occlusions can be clearly displayed. We also design an interaction interface to analyze differences from diverse perspectives. We demonstrate the effectiveness of our approach by applying it to two real-world applications.

Index Terms: Computer Applications [J.3]: Life and Medical Sciences

1 INTRODUCTION

Diffusion Tensor Imaging (DTI) [3] is a non-invasive *in vivo* magnetic resonance imaging technique that measures the diffusion of water in biological tissues. In tissues containing fibrous structures such as the brain white matter, the diffusion is faster along the fibers and slower in the directions perpendicular to the fibers. By fitting the distribution of water molecules with a Gaussian model and representing this Gaussian model as a second-order tensor, a DTI tensor volume can be reconstructed from the raw diffusion weighted image (DWI) volume [27]. Furthermore, tracing the paths through the entire tensor volume produces a collection of DTI fibers. This process is known as fiber tractography or fiber tracking [2], which has been proven to be a useful technique for analyzing anatomical connectivity.

Despite of its potential, DTI remains limited in clinical applications. Uncertainty is a major reason. DTI fibers vary from subject to subject due to the variations in anatomy, and from scan to scan because of different subject positions, motions and noises. These fibers are also sensitive to various parameters in tractography such as the seeding locations and anisotropy thresholds [34]. Comparison can help users identify the differences and understand the uncertainty among DTI models. Clinical applications of DTI fiber models will be more likely after the domain users understand the sources of uncertainty and how these fiber models are affected by the uncertainty.

Representing and visualizing differences within a collection of DTI datasets is not a trivial task. Direct comparison of 3D DWI or DTI volumes [21, 36] requires accurate alignment and loses connectivity information along fibers. Explicitly depicting geometrical differences among DTI fibers in the 3D space [5, 10] is hindered by the spatial complexity of the dense fibers. Comparison of quantitative tractography metrics [9] such as average fiber length lacks the ability to locate regions of significant differences.

Projection techniques have been widely used to construct a visual representation of a high-dimensional dataset in a way that the projection layout respects the proximity between instances in the source dataset. They provide a holistic view for the essence of a high-dimensional dataset. Successful application in visualization include document exploration [28], data orgranization [29], and subspace exploration [1]. Recent work extends this scheme into the exploration of DTI fiber models [6, 31]. However, these approaches are designed to explore the content of a single fiber model and cannot be employed to analyze multiple fiber models. The main reason is that different fiber models do not share a common space for projection and comparison.

In this paper, we presents a difference visualization approach for DTI fiber models. To summarize our method ...

The contributions of this paper are:

- A cluster-projection routine to build a occlusion-free representation for comparison and regions of differences estimation;
- An integrated visualization interface that enable users to explore differences from different perspectives in an intuitive way.

The remaining parts are organized as follows. Section 2 summarizes the related work. Our approach is described in Section 3. A visual exploration system is presented in Section 4. The results of our approach and experts' feedback are discussed in Section 5. Finally, we conclude this paper in Section 6.

2 RELATED WORK

Our work is related to several areas of prior research including comparative visualization, uncertainty visualization, and DTI fiber model exploration.

2.1 Comparative Visualization

In the last years, a wide variety of approaches have been developed in the field of comparative visualization. Gleicher et al. [15] presented a general taxonomy of visual designs for comparisons and summarized these designs into three categories: *Juxtaposition*, *Superposition*, and *Explicit Encoding*. Zhou et al. [39] outlined a group of comparison metrics for quantifying the difference between a visualization of a computer simulation and a photographic image. Verma and Pang [37] proposed several possible solutions for comparative flow visualization at image level, data level, and feature level. Malik et al. [24] introduced a novel multi-view design for comparing and visualizing gray values and edges of several 3DCT datasets simultaneously. Their method first divides the plane into hexagonal regions. Each region is further subdivided into multiple sectors to depict details from different datasets. This design allows users identify difference very easily but limited by the number of datasets. Schmidt et al. [35] proposed an approach for the comparative visualization of multiple images. Their technique overcomes the scalability issues pertaining to number of objects for comparison, and allows users to perform detailed cluster analysis in the regions of significant differences. Oelke et al. [25] designed a glyph representation called topic coins to encode information necessary for comparative document analysis. Piringer et al. [30] developed an interactive approach for comparative visual analysis of 2D function ensembles.

In the filed of DTI study, comparison is an important means to locate changes related to development, degeneration, and disease.

One pioneering work by Silva et al. [10] compares the generated fibers in 3D space directly and uses saturation to indicate the magnitude of differences between corresponding points. This method is simple and intuitive, but only focuses on fiber structures and may result in visual clutters. In order to investigate the diffusion properties along fibers, group statistical analysis [8, 16] is performed after aligning datasets and representing fibers with continuous functions. The key idea behind this method is that fibers are represented with a simplified form (like B-spline) to facilitate statistical comparison.

Comparing multiple volumetric datasets typically requires a volume registration step. To study the diffusion properties such as Fractional Anisotropy (FA) for multiple subjects, Smith et al. [36] presented a voxelwise analysis framework via a nonlinear registration flowed by projection onto a skeleton. Nevertheless connectivity information are ignored by this method. In addition to the study on DTI volumes, there has been some work on general-purpose group analysis of geometrical or volumetric datasets. For instance, Elvins et al. [12] proposed to use a density histogram to describe a volume dataset. Though simple, it provides low discrimination power. Other different feature descriptors have been proposed to accomplish similarity assessment, including transformational [14], topological [18], and statistical [26] signatures. Different from these methods, our approach produces a continuous 2D map as a signature of a 3D fiber model for further comparative analysis.

2.2 Uncertainty Visualization

Analyzing and visualizing the differences among the datasets plays a central role for studying the uncertainty. General techniques employ visual variables [17, 32], glyphs [19, 33], and animations [23] to depict uncertainty. Then uncertainty in the context of DTI datasets arises from multiple aspects such as noise, motions, variations in anatomy, and parameters in fiber tracking. Quantification of the uncertainty usually targets the characteristics of the diffusion tensors including the main direction and fractional anisotropy. Friman et al. [13] employed a Bayesian framework to model the uncertainty associated with fiber paths. Chung et al. [7] exploited the non-parametric statistical technique Bootstrap to quantify uncertainties of diffusion tensor parameters. Later wild bootstrap approach [38] that requires only one acquisition of DWIs while achieving similar effects as the standard Bootstrap methods was used to measure uncertainty. Brecheisen et al. [34] designed a visualization tool to interactively study the influence of parameters on fiber tracking. To show the shape uncertainty in fiber tracking, illustrative visualization methods were exploited to explicitly depict uncertainties in the 3D fiber space [4].

2.3 DTI Fiber Model Exploration

Exploring and manipulating a DTI fiber model in 3D space poses many challenges, especially on providing intuitive interaction. Embedding the fibers into a 2D space with projection techniques has been demonstrated to an effective way to study fibers. Chen et al. [6] designed a novel interface based the MDS technique to facilitate quick and accurate 3D fiber selection on a 2D plane. Similarly, Jianu et al. [20] introduced a visual exploration paradigm by embedding 3D fibers into a 2D plane to reduce navigation efforts. Poco et al. [31] introduced the *Local Affine Multidimensional Projection (LAMP)* [22] technique to support fast visual exploration of large collection of DTI fibers. Demiralp et al. [11] presented a 2D path representations base a planar projection technique for studying fiber dataset on a web interface. The 2D visual representation captures the essence of the source dataset and is free of occlusion during interaction and exploration. However, most of these approaches focus on single fiber model exploration. This paper advances a computation efficient two-phase projection technique to compare multiple fiber models.

3 Our Approach

4 Visualization and Interactions

5 Results and Discussions

6 Conclusion

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